Automated Power Assessment for Helicopter Turboshaft Engines

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Abstract

An accurate indication of available power is required for helicopter mission planning purposes. Available power is currently estimated on U.S. Army Blackhawk helicopters by performing a Maximum Power Check (MPC), a manual procedure performed by maintenance pilots on a periodic basis. The MPC establishes Engine Torque Factor (ETF), an indication of available power. It is desirable to replace the current manual MPC procedure with an automated approach that will enable continuous real-time assessment of available power utilizing normal mission data. This report presents an automated power assessment approach which processes data currently collected within helicopter Health and Usage Monitoring System (HUMS) units. The overall approach consists of: 1) a steady-state data filter which identifies and extracts steady-state operating points within HUMS data sets; 2) engine performance curve trend monitoring and updating; and 3) automated ETF calculation. The algorithm is coded in MATLAB (The MathWorks, Inc.) and currently runs on a PC. Results from the application of this technique to HUMS mission data collected from UH-60L aircraft equipped with T700-GE-701C engines are presented and compared to manually calculated ETF values. Potential future enhancements are discussed.

Nomeclature

ETF	engine torque factor
HIT	Health Indicator Test
HUMS	Health and Usage Monitoring System
KIAS	knots indicated airspeed
MPC	Maximum Power Check
N	number of *TGT* bins
Ng	gas generator speed
Np	power turbine speed
OAT	outside air temperature
SHP	shaft horsepower
$SHP_{nom,i}$	nominal engine *SHP* value of ith bin
STR	specification torque ratio
TGT	Turbine Gas Temperature
$TGT_{i,k}$	*TGT* input to i^{th} bin at time k
$\overline{TGT}_{i,k}$	Average *TGT* in i^{th} bin at time k
TLM	table lookup model
TTV	target torque value
W	*TGT* bin weighting matrix used in residual curve fit

$\alpha_{i,k}$	weighting of ith *TGT* bin at time k
f	function of nominal *SHP* at given *TGT*
g	function of lapse rate at given *TGT*
m_{eng}	residual curve fit scale factor
$m_{LR,i}$	residual curve fit lapse rate adjustment for i^{th} bin
y_{SHP}	vector of $\overline{\Delta SHP}_{i,k}$ values contained in *TGT* bins at time k
ΔSHP	*SHP* residual (actual—nominal)
$\Delta SHP_{i,k}$	ΔSHP input to i^{th} bin at time k
$\overline{\Delta SHP}_{i,k}$	average ΔSHP in i^{th} bin at time k
σ	measurement standard deviation

Superscript

^	estimated value

Subscripts

i	*TGT* bin index
k	time step index of steady-state data

Introduction

Over their lifetime of use, the level of power that individual helicopter turboshaft engines can produce will vary. There are several factors that can contribute to this including the initial performance level of the engine when it enters service, natural deterioration effects due to wear and fouling of turbomachinery blades, vanes and seals, component faults, and periodic in-service maintenance actions performed on the engine. Operation in desert sandy environments is a particular area of concern as it can rapidly accelerate engine deterioration and performance losses (refs. 1 to 3). Helicopter operators require a means to assess available engine power because it is critical to overall vehicle operation and safety. They rely on this information in part to make decisions regarding mission planning and the scheduling and performance of engine maintenance and overhauls.

The U.S. Army currently estimates available power on their helicopter turboshaft engine assets by manually performing a procedure known as a MPC. An MPC is performed when an engine is first installed on the aircraft, after an engine undergoes a maintenance action, and after an engine fails a Health Indicator Test (HIT). The HIT check is a ground-based operational check performed daily to trend engine performance, verify proper operation of the anti-icing bleed and start valve, and to identify any significant deviations in engine perform-

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ance. In order to pass the HIT check, an engine's turbine gas temperature (*TGT*) must be within acceptable operating limits. The MPC, unlike the ground-based HIT check, is performed in flight by a maintenance pilot and entails a multi-step process with a relatively heavy pilot workload. During the MPC, power to one engine is reduced while power to the engine being checked is increased until that engine encounters an operational control limit. At this point the pilot is required to hold the vehicle at a fixed altitude, airspeed and power setting while allowing engine operation to stabilize, and then record the necessary vehicle and engine operating parameters. Next, relying on information obtained from engine performance tables provided in the maintenance manual to adjust for the recorded altitude and outside air temperature (*OAT*) conditions, the pilot manually calculates ETF. ETF provides an indication of the actual power that an engine is capable of producing relative to the rated power of the engine. A detailed summary of the MPC for the UH-60HL aircraft can be found in the T700 engine maintenance manual (ref. 4).

It is desired to replace the current manual MPC with an automated approach that will enable continuous real-time assessment of available engine power. There are multiple benefits to having a reliable automated power assessment capability including enabling the optimal scheduling and performance of engine maintenance, improving asset availability, reducing reliance on specialized maintenance pilots and operating procedures, and avoiding exposure to hostile fire which can be incurred when performing manual MPCs in theater. Towards this goal, the U.S. Army Research Laboratory and the U.S. Army Aviation and Missile Research Development Engineering Center, Aviation Engineering Directorate have worked in conjunction to develop a methodology for continuous real-time power assessment in helicopter turboshaft engines. This approach has been developed for application to T700-GE-701C turboshaft engines installed on UH-60L Black Hawk helicopters. The T700-GE-701C engine serves as the power plant for the latest UH-60L Black Hawk variants and AH-64A/D Apaches (ref. 5). This 1800 hp-class engine is a modular two-spool design consisting of a gas generator section and a free power turbine. The engine is controlled through the interaction of an Electrical Control Unit and a Hydromechanical Control Unit. The automated power assessment methodology presented in this paper has been designed to process parameters currently recorded and available within helicopter HUMS and to produce an automated estimate of ETF. Some past work utilizing T700 HUMS data to assess overall engine condition was reported by Karvounis and Frith (ref. 6). In that reference, a model-based fuzzy logic approach for assessing the overall engine condition was presented.

This paper is organized as follows. First, a description of the automated power assessment methodology is presented and the individual elements of the methodology are described in detail. Next, results from the application of the technology to actual helicopter engine HUMS data are presented and the accuracy of automatically calculated ETF results are compared to available manually calculated ETF values. Finally, development and maturation steps necessary to field a practical implementation of the technology are discussed.

Automated Power Assessment Approach

The automated power assessment architecture is shown in figure 1. The automated technique is designed following an approach very similar to the one applied to manually calculate ETF. The fundamental difference is that the automated procedure estimates engine power at the limiting temperature condition based on the extrapolation of data obtained during normal mission profiles, whereas the manual procedure requires the engine to be physically operated at a limit condition. A prototype version of the automated power assessment methodology has been developed in the MATLAB environment and currently runs on a PC. Although the current implementation of the technology does not run in real-time, it utilizes coding constructs to facilitate potential future real-time implementation of the technology. The elements of the architecture consist of: 1) a steady-state data filter; 2) engine performance trend monitoring; and 3) automated ETF calculation logic. The steady-state data filter monitors and extracts steady-state segments from the incoming HUMS data stream. Each time a steady-state segment is identified it is provided to the engine performance trend monitoring logic which uses it to update a shaft horsepower (*SHP*) versus *TGT* performance curve for the individual engine. ETF is calculated automatically by determining the limiting power condition (the point where the temperature control limit will be encountered), and converting this information into an estimate of ETF using the same procedure as the manual approach. The following sections of this report will discuss each function of the overall architecture in more detail.

Steady-State Data Filter

Helicopter engines will experience a broad range of operating conditions during the course of a normal mission, including periods of transient and of quasi-steady-state operation. An algorithm was developed to classify steady-state operation, which is defined by a set of constraints being met simultaneously. It was designed to have the ability to process HUMS data in real time. This steady-state data filter algorithm uses only the subset of recorded HUMS parameters directly related to engine performance. A summary of the HUMS
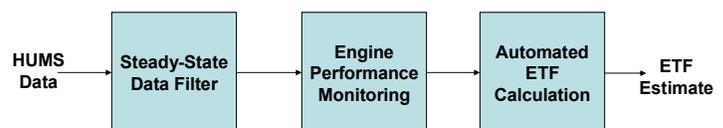
Figure 1.—Automated power assessment architecture.

parameters utilized, and constraints applied by the steady-state data filter, is given in table 1. The steady-state data filter relies on the calculated standard deviation (σ) of select parameters contained in the incoming HUMS data stream to determine steady-state operation. It first assesses the incoming data to insure that the anti-ice bleed valve is turned off since that will impact overall engine performance. It also checks to make sure corrected gas generator speed, Ng, is above 90 percent to exclude startup and idle operating points. If these criteria are satisfied, a window of the incoming data is buffered for subsequent analysis. The minimum buffered data window must be 15 sec. Once the minimum data window length is achieved, the mean and standard deviation of each parameter contained in the buffered window are calculated. The standard deviations are compared against the defined threshold criteria shown in table 1. If the steady-state criteria are not satisfied, the steady-state data filter advances the window one time step, maintaining the most recent 15 sec of data, and the evaluation criteria are re-applied. If the standard deviation of each parameter is less than its specified threshold, the data in a window are considered to be in steady-state. The next time slice of data is appended to the buffered data window and the evaluation procedure is repeated on the augmented window of data. This process is repeated at each time step, extending the length of the buffered window up until any of the defined steady-state criteria are violated. At that point the mean values of the previous time step are extracted for use in subsequent engine performance assessments, and the steady-state filter resumes monitoring of the incoming data stream for the next segment of steady-state data.

TABLE 1.—STEADY-STATE DATA FILTER
PARAMETERS AND APPLIED CONSTRAINTS

Parameter	Constraint
Anti-ice bleed valve	Off
Ng, corrected	> 90%
Data segment window	≥ 15 sec
Torque	σ < 0.5%
Ng	σ < 0.2%
TGT	σ < 1.5 °C
Np	σ < 0.2%
Pressure altitude	σ < 30 ft
Airspeed	σ < 4 knots
OAT	σ < 1 °C

The steady-state data filter logic is designed to facilitate on-line real-time processing of streaming HUMS data (as opposed to post-processing the data in a batch processing mode): the mean and standard deviation values of the HUMS parameters are calculated in a recursive fashion. This requires only the mean and standard deviation values from the previous time step, the most recent parameter sample, and in the case of the

moving 15 sec window the oldest parameter sample. Recalculating the mean and standard deviation values each time step based upon all samples stored in the buffer (batch mode) would have resulted in considerable processing overhead. Some issues which complicate the recursive logic are that not all of the parameters are sampled at the same frequency in a synchronized manner, and occasional data dropouts in the incoming stream were encountered. The logic has been designed to be robust to these issues.

After initial development, the steady-state data filter was applied to available T700-GE-701C helicopter engine HUMS data sets. At this time an interesting observation was made when comparing the number of steady-state data points the filter identified from two engines installed on the same aircraft. Although the two engines were operated in a very similar fashion, the steady-state data filter consistently identified more steady-state points within the operating history of one engine than the other. Upon closer observation it was discovered that the primary factor causing this discrepancy was the variance in engine sensor measurements, particularly the torque sensor measurement. To address this issue a second order low-pass filter was added to pre-process the incoming HUMS data provided to the steady-state data filter. The effect of adding this filter is two-fold: it provides improved consistency in the number of points identified from each engine, and it also allows more steady-state points to be identified, particularly at high power regions where the sensor measurements tend to exhibit more variance.

An example of the steady-state data extracted from a single flight of HUMS data is shown in figure 2. Here SHP versus TGT data are plotted. Because engine operation is strongly influenced by the ambient operating conditions, *corrected* parameters (ref. 7) are shown here and throughout the paper to reduce data scatter and enable easier analysis. In figure 2, the cyan points represent all of the raw SHP versus TGT data collected during the mission while the red points represent the steady-state points identified by the steady-state data filter. Due to transient operating excursions a considerable amount of variation is evident in the raw data. The steady-state points represent a much tighter clustering around the engine steady-state operating line.

A 3-D scatter plot of the steady-state data points identified from a single engine over a 6 month period is shown in figure 3. Once again corrected SHP is plotted versus corrected TGT. In this plot the color denotes the date on which the steady-state point was collected, according to the color bar on the right-hand side of the plot. In this engine an abrupt shift in performance is noted in the September time frame. The authors have no knowledge of the actual cause for this performance shift, although it has been hypothesized that it may be due to installation of hardware such as an inlet barrier filter since this engine, and the opposite engine installed on the same aircraft, both exhibit a similar shift on the same date.
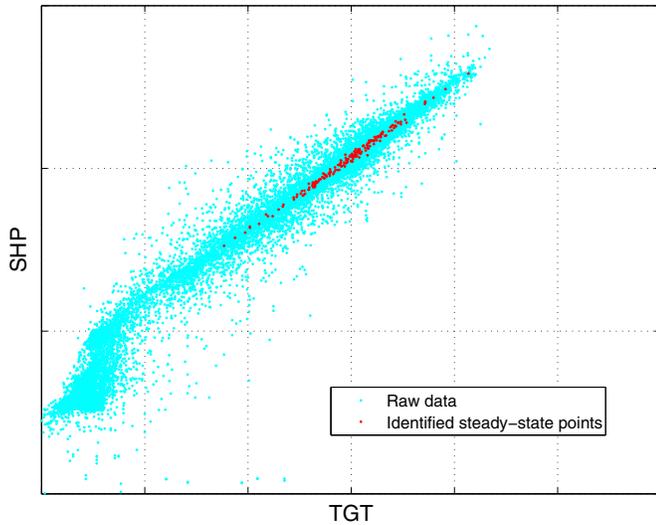
Figure 2.—Comparison of raw and steady-state *SHP* versus *TGT* data collected from a single flight.
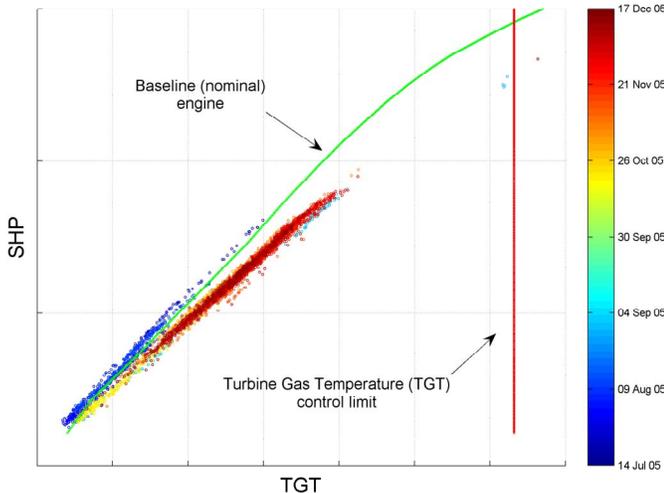
Figure 3.—Example of the steady-state *SHP* versus. *TGT* data collected from an individual engine over 6 months.

The steady-state data filter was applied to HUMS data collected from 15 different vehicles (30 engines) encompassing 1688 missions covering 2813 hr. An average of approximately 40 steady-state points per engine, per mission, were identified by the steady-state data filter.

Engine Performance Monitoring

Each time an engine steady-state data point is identified, it is compared to nominal engine performance to generate an engine performance residual. This residual, denoted as Δ*SHP*, represents the delta, or difference, in corrected shaft horsepower between the actual engine at the identified steady-state operating point, and a nominal engine operating at the same condition. In the automated power assessment architecture, nominal engine performance is represented by a four input

Table Lookup Model (TLM). The four inputs to this model are pressure altitude, knots indicated airspeed (*KIAS*), *OAT*, and corrected *TGT*. As an output the model produces the corresponding *SHP* of a nominal engine at the given operating conditions. The TLM is constructed based on outputs from the T700-GE-701C steady-state cycle deck and is coded in MATLAB using interpolation functions. This implementation provides a compact and efficient representation of nominal steady-state engine performance over a broad range of operating conditions.

After the corrected shaft horsepower performance residual is calculated it is used to update an engine performance curve representing corrected *SHP* versus corrected *TGT* performance for the individual engine. To accomplish this function, a curve fit through the shaft horsepower performance residuals versus power setting (defined by corrected *TGT*) is performed, and then this residual curve fit is added to the performance curve of a nominal engine to construct a performance curve unique to each individual engine:

Engine Performance =
Nominal Engine Performance + Residual Curve Fit

The steps required to accomplish the engine performance curve fit are as follows:

1. The operating range of the engine is partitioned into uniformly spaced corrected *TGT* "bins."
2. Each time a new steady-state data point is found, it is corrected and referenced against the corrected *SHP* of a nominal engine, as defined by the TLM, to produce a Δ*SHP* residual.
3. The Δ*SHP* residual is then sorted into the appropriate *TGT* bin, and used to update the average *TGT* and Δ*SHP* values within the respective bin. A bin becomes "active" once it receives its first steady-state point.
4. Updates of the bin *TGT* and Δ*SHP* averages are performed in an exponential moving average fashion as shown in equation (1).

$$\overline{TGT}_{i,k} = \alpha_{i,k} \cdot \overline{TGT}_{i,k-1} + (1 - \alpha_{i,k}) \cdot TGT_{i,k}$$
$$\overline{\Delta SHP}_{i,k} = \alpha_{i,k} \cdot \overline{\Delta SHP}_{i,k-1} + (1 - \alpha_{i,k}) \cdot \Delta SHP_{i,k}$$

(1)

In this equation $\overline{TGT}_{i,k}$ is the *TGT* average for bin *i* at time step *k*, $\alpha_{i,k}$ is the exponential forgetting factor for the data contained in bin *i* at time step *k*, and $TGT_{i,k}$ is the corrected *TGT* value of the incoming steady-state point added to bin *i* at time step *k*. Similar definitions apply for the parameters associated with Δ*SHP*. It should be noted that in these equations the forgetting factors, $\alpha_{i,k}$, are variable and unique to each bin. At the beginning of each flight the forgetting factor of each bin is scaled down. If a new steady-state data point is found during a flight it is used to update the corresponding bin averages as shown in equation (1), and then the specific bin

forgetting factor, $\alpha_{i,k}$, is increased a fixed amount. An upper constraint is placed on $\alpha_{i,k}$ so that they may not exceed 0.9. This process of adjusting the bin forgetting factors has several desirable effects: 1) it places more emphasis on the new data and less on older data allowing the bin average parameters to respond to engine performance changes over time; 2) it places more emphasis on incoming data in sparsely populated bins, and less emphasis on incoming data in richly populated bins; and 3) it can be directly used in the weighted least squares curve fit computation (to be discussed below).

5. After a new steady-state data point has been processed and used to update the corresponding parameter averages within the associated bin, a weighted least squares curve fit through the ΔSHP versus TGT values of all the active bins is performed, as shown below. If a defined bin contains no data (inactive) it is excluded from the curve fit. Equation (2) represents the general curve applied in the automated curve fit.

$$\overline{\Delta SHP}_{i,k} = SHP_{nom,i} \cdot m_{eng} \cdot m_{LR,i} + b_{eng} \qquad (2)$$

This equation was defined using similar parameter relationships to those in the manual ETF procedure. This includes referencing ΔSHP to nominal, or rated, SHP with an additional adjustment included to capture power lapse rate effects. Power lapse rate reflects the change in the ratio of actual to rated power with operating condition. It is uniquely defined for a particular engine model based on experimental testing of deteriorated engines. The scale factor $m_{LR,i}$ represents the lapse rate adjustment at the $\overline{TGT}_{i,k}$ power setting of bin i; it is derived from information provided in the T700 maintenance manual (ref. 4). In equation (2) the $\overline{\Delta SHP}_{i,k}$ residual at any given power setting (as established by $\overline{TGT}_{i,k}$) is also referenced, or scaled, to the SHP of a nominal engine ($SHP_{nom,i}$) operating at the same TGT setting using an overall curve fit scale factor adjustment, m_{eng}. An additional curve offset adjustment, b_{eng}, is included in equation (2) to improve the overall quality of the curve fit. Linear interpolation functions, denoted as f and g, are used to calculate $SHP_{nom,i}$ and $m_{LR,i}$ respectively at the $\overline{TGT}_{i,k}$ conditions for each bin:

$$SHP_{nom,i} = f\left(\overline{TGT}_{i,k}\right)$$
$$m_{LR,i} = g\left(\overline{TGT}_{i,k}\right) \qquad (3)$$

6. Based upon the residual function described in equation (2), a weighted least squares fit through the $\overline{\Delta SHP}_{i,k}$ versus $\overline{TGT}_{i,k}$ data contained in the bins is calculated as shown in equation (4).

$$\begin{bmatrix} \hat{m}_{eng} \\ \hat{b}_{eng} \end{bmatrix} = \left[A^T W A\right]^{-1} A^T W y_{SHP} \qquad (4)$$

where

$$A = \begin{bmatrix} SHP_{nom,1} \cdot m_{LR,1} & 1 \\ SHP_{nom,2} \cdot m_{LR,2} & 1 \\ \vdots & \vdots \\ SHP_{nom,N} \cdot m_{LR,N} & 1 \end{bmatrix}$$

$$W = \begin{bmatrix} \alpha_{1,k} & 0 & \cdots & 0 \\ 0 & \alpha_{2,k} & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & \alpha_{N,k} \end{bmatrix}$$

$$y_{SHP} = \begin{bmatrix} \overline{\Delta SHP}_{1,k} \\ \overline{\Delta SHP}_{2,k} \\ \vdots \\ \overline{\Delta SHP}_{N,k} \end{bmatrix}$$

In the above equation N represents the number of active bins, and the weighting matrix, W, places more emphasis on bins that are richly populated and/or contain newer data, and places less emphasis on those bins that are sparsely populated and/or contain older data.

7. The $\hat{m}_{eng}$ and $\hat{b}_{eng}$ values estimated in equation (4) are substituted into equation (2) to produce a residual curve of ΔSHP versus TGT. This curve is then added to the SHP versus TGT curve of a nominal engine. This produces a corrected SHP versus corrected TGT performance curve based upon the current condition of the engine.

Following the steps outlined above produces a corrected SHP versus corrected TGT curve unique to the individual engine being monitored. Furthermore, the curve is able to automatically update over time as the engine undergoes performance changes.

Figure 4 shows an example of the weighted least squares curve fit generated for an engine at a particular instant in time following the steps outlined above. The vertical dashed lines denote the partitioning of the TGT bins. In the top plot the circles denote the location of the average ΔSHP and TGT residual for each bin, while the size of the circles denotes the weighting assigned to each bin. Larger circles are weighted more heavily. The solid blue line is the weighted least squares curve fit through the residuals of the data set. The knee in this curve corresponds to the point where the slope changes direction due to the inclusion of lapse rate effects in the curve fit. (Note: Below this point $m_{LR,i}$ values equal 1.0 and thus have no effect on the shape of the residual curve fit). The bottom plot shows the corresponding SHP versus TGT curve for the engine (in blue) produced by adding the residual curve fit to the SHP versus TGT curve of a nominal engine. As a
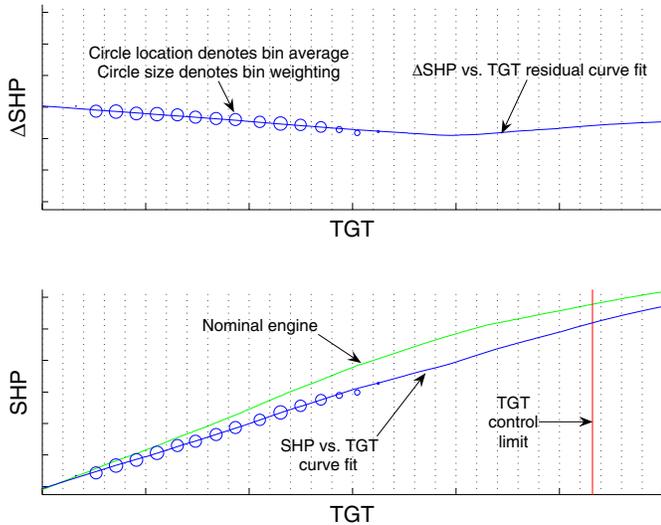
Figure 4.—Example of *SHP* versus *TGT* curve fit.

comparison, the *SHP* versus *TGT* curve of a nominal engine is also shown (green curve). Also included is the *TGT* control limit (red vertical line). In this plot, and for ETF calculation purposes, the data are corrected to the 0 ft, 120 knots, 15 °C condition. (Note: The data are corrected to the 120 knots condition to be consistent with the MPC procedure which is specified to be conducted at this airspeed (ref. 4)). It should be emphasized that the actual *TGT* limit defined and applied within the engine control unit is a physical limit based on the material properties of the turbine blades, and is applied to the *uncorrected* value of *TGT*.

Automatic Engine Torque Factor Calculation

The final step in the automated power assessment methodology is the automated calculation of Engine Torque Factor (ETF). This is performed in a manner analogous to the manual MPC procedure described in the T700 maintenance manual (ref. 4). Each time the engine *SHP* versus. *TGT* performance curve is updated, a new ETF value is calculated via the following steps:

1. The *SHP* setting where the *TGT* control limit will be encountered is estimated. This is accomplished by determining the *y*-axis (*SHP*) value where the *SHP* versus *TGT* curve (blue line in fig. 4) and the engine *TGT* control limit (red line in fig. 4) intersect—this is the limiting power condition. This *SHP* value is then converted to Torque assuming that the power turbine speed, *Np*, is 100 percent.

2. A Specification Torque Ratio (STR) is calculated by dividing the limiting torque condition calculated in step 1 by the Target Torque Value (TTV). The TTV is based on the

rated power that all engines are guaranteed to produce upon entry into service. Since the data have been corrected to the 0 ft, 120 knots, 15 °C operating condition, the TTV applied in the automated calculation is fixed, and corresponds to the TTV for a UH-60L T700-GE-701C engine operating at these same conditions as specified in the T700 maintenance manual (ref. 4).

3. The linear relationship specified in the maintenance manual is used to convert STR to ETF assuming operation at the 15 °C *OAT* condition.

Examples of the automatically estimated ETF time histories produced for the two engines installed on the same aircraft are shown in figure 5. These are represented by the red (engine 1) and blue (engine 2) points in the figure. For this particular aircraft, two missions within the available HUMS data sets contained MPC procedures. Relying on the associated altitude, *OAT* and torque values recorded within the HUMS data at the time of the MPC, the authors manually calculated the corresponding ETF values following the procedure specified in the T700 maintenance manual. These manually calculated ETF values (two points for each engine) are represented by the circles shown in the figure. For this particular aircraft, the automated and manual ETF results agree very well for engine 2. However, for engine 1 the values calculated by the automated procedure are lower than the manually calculated ETF values.

It should be clarified that some of the ETF values shown in figure 5 exceed 1.0 even though the actual MPC procedure (ref. 4) specifies that for any engine producing an STR value greater than 1.0, an ETF value of 1.0 should be recorded, regardless of the STR magnitude. For the results shown in this paper that has not been done in order to gain a better assessment of how accurately the automated power assessment procedure predicts the true limiting power condition of the engine. Therefore, all automated *and* manual ETF results shown in this document have been produced by applying the linear conversion relationships between STR to ETF. This produces ETF values greater than 1.0 in some instances. In the figure it can also be observed that both engines exhibit an abrupt shift in operating performance around the September timeframe. Note that engine 2 is the same engine for which example steady-state data were shown in figure 3. Periodic shifts in engine performance are not atypical, several of the engines analyzed were found to exhibit abrupt decreases or increases in performance periodically. To be robust to these occurrences, automated reset logic was added to the engine performance monitoring logic. If at any time the mean squared error between the curve fit and the data exceeds a specified threshold, the residual bins are cleared (reset) and the trending process starts over. This allows the performance monitoring logic to respond more rapidly, and accurately, to large and abrupt engine performance changes.
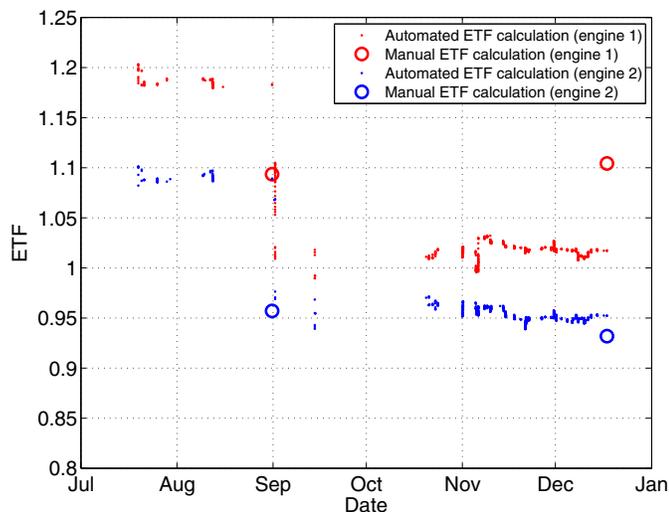
Figure 5.—Example of automated ETF time histories.
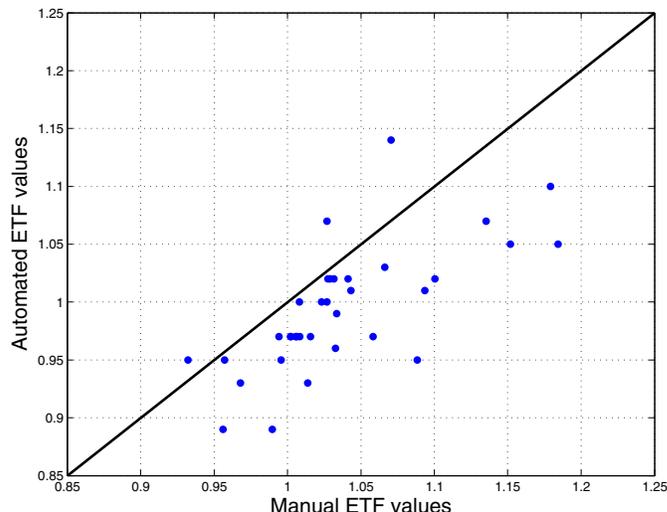
Figure 6.—Comparison of automated versus manual ETF calculations.

Results—Comparison of Automated Versus Manual ETF Calculations

The automated ETF calculation technique was applied to the HUMS data collected from 30 engines. In these data sets a total of 35 maximum power check points were identified and the corresponding ETF values were manually calculated. Figure 6 compares the automated and manually calculated ETF values produced for the 35 MPC cases. The solid line (slope = 1.0) provides a reference for perfect agreement between the two approaches. From the figure it can be observed that in most cases the automated ETF value is less than its manually calculated ETF counterpart. The average absolute estimation error between the manual and automated approaches is 5.1 percent. If ETF values are truncated above 1.0 as specified by the maintenance manual the average absolute estimation error is 1.9 percent considering all 35 points, and is 4.3 percent when just considering the 7 points below 1.0 ETF.

Discussion

Additional development and validation is required to mature this technology to the point of practical application. This includes further investigation of several areas of uncertainty that may contribute to the differences found between the automated and manual ETF calculations. For the purpose of this study it was not known which engines did, or did not, have auxiliary hardware installed. For example, infrared suppression systems and inlet barrier filters can affect overall engine performance and need to be accounted for in the process. The model used to represent nominal engine performance needs to accurately capture the performance effects of such hardware when installed. Furthermore, the automated power assessment logic must be configured to account for the installation or removal of such hardware as well as for

different modes of operation (e.g., inlet barrier filter bypass doors open versus closed). Another area of uncertainty is the performance curve fit applied and used to estimate the engine limiting power condition. While this approach exhibits reasonable accuracy in approximating engine performance in the low to intermediate power region where HUMS data are available, its accuracy in matching engine performance at high power conditions is somewhat uncertain due to the limited amount of high power HUMS data available for this study. It is also uncertain how well the applied lapse rate effects capture variations in engine performance as a function of power setting. These issues should be addressed through the thorough testing and evaluation of the overall approach under a range of engine deterioration levels, ambient operating points, power settings and hardware configurations. The applied steady-state data filtering and data correction approaches also introduce a degree of uncertainty. There is a natural trade-off between the defined steady-state constraints and the quantity and quality of the steady-state data. Looser constraints are expected to yield more points, although the data will contain greater variance, contributing greater uncertainty in the overall ETF estimates. Another factor contributing to the effectiveness of the algorithm is related to the operation of the individual engine. The limiting power condition of an engine from which high power points are collected will probably be estimated more accurately than that of an engine from which only lower power data are available. Also, for this approach all steady-state data have been corrected to a single engine performance curve to enable trending of data collected at different operating points. While parameter correction helps to significantly reduce variance in the data, it does not collapse the data to a perfect "fit," making the approach susceptible to biases introduced during the correction process. Another area of uncertainty is that the automated approach assumes that all engines have the same TGT limit

setting. In reality there is a range for the TGT limit due to hardware variation, and the actual limit setting will directly affect the maximum amount of power an engine can produce. If the true TGT limit for an individual engine is known, it can be incorporated into the automated power assessment process, but if unknown and different from the assumed TGT limit, it can introduce differences between the automated and manually calculated ETF values.

Conclusions

A prototype automated power assessment technique for helicopter turboshaft engines has been developed and demonstrated. The objective of this technology is to provide real-time continuous assessment of available engine power. To perform this function, it uses normal mission data currently collected within HUMS units without the need for specialized maintenance procedures. The approach applies steady-state data filtering logic to extract regions of steady-state engine operation, and uses this information to establish and trend a performance curve unique to an individual engine. The performance curve is used to estimate the engine's limiting power condition and calculate ETF, an indication of available power. The automated technique has been applied to HUMS data collected from T700-GE-701C engines installed on UH-60L aircraft. Results from this study indicate that the automated approach typically underestimates the ETF values obtained via manual calculations. Additional development and validation is required to mature the technology to the level where it would be suitable for actual implementation.

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14. ABSTRACT
An accurate indication of available power is required for helicopter mission planning purposes. Available power is currently estimated on U.S. Army Blackhawk helicopters by performing a Maximum Power Check (MPC), a manual procedure performed by maintenance pilots on a periodic basis. The MPC establishes Engine Torque Factor (ETF), an indication of available power. It is desirable to replace the current manual MPC procedure with an automated approach that will enable continuous real-time assessment of available power utilizing normal mission data. This report presents an automated power assessment approach which processes data currently collected within helicopter Health and Usage Monitoring System (HUMS) units. The overall approach consists of: 1) a steady-state data filter which identifies and extracts steady-state operating points within HUMS data sets; 2) engine performance curve trend monitoring and updating; and 3) automated ETF calculation. The algorithm is coded in MATLAB (The MathWorks, Inc.) and currently runs on a PC. Results from the application of this technique to HUMS mission data collected from UH-60L aircraft equipped with T700-GE-701C engines are presented and compared to manually calculated ETF values. Potential future enhancements are discussed.

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Aircraft engines; Systems health monitoring; Gas turbine engines; Flight safety

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